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Assessment of Post-Outage Congestion Risk of Wind Power with Dynamic Line Ratings

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Abstract— **One of the factors hindering the large scale integration of wind power is the post contingency congestion of a network due to limited availability of network capacity and auxiliary constraints. Under such conditions, the network operators can potentially request a curtailment of wind farm output if the remedial strategies fail. The paper investigates this problem in detail and proposes a mathematical framework to capture the post contingency spare capacity of network assets that is required to limit the wind curtailment. The proposed approach incorporates stochastic variation in asset thermal rating; models network congestion, and quantifies the risk of congestion using an extended version of conic-quadratic programming based optimization. The results suggest that the wind utilization can be maximized if the networks are operated 30-50% less than the nominal rating of the assets.**

Index Terms— **dynamic line ratings, risk of congestion, quadratic programming, wind power generation,**

I. INTRODUCTION

Network congestion is an undesirable result of insufficient capacity being available on a network to transport electricity from generation to loads. It leads to highly variable locational marginal prices (LMP) at nodes usually with high prices at load points which are affected by congestion compared to those which are not. In systems with large amount of wind power, network congestion hinders effective integration and utilization of wind as extra wind generated has to be curtailed thereby leading to uncertainty in revenue for wind power producers. The dynamic nature of wind results in large variations in power output over a short period of time, which makes effective utilization of wind an even bigger challenge in congested networks.

Network congestion has a greater impact in networks under contingency. When a contingency occurs in a branch, the remaining branches in the network can experience greater loading and be at a higher risk of network congestion. While traditional security analysis uses the N – 1 criterion this does not account for variation in outputs of wind generators thereby leading to post contingency congestion and curtailment of wind. Therefore, even when a network seems to have no congestion and utilizes wind effectively, there is a high risk that any contingency will drastically change the situation.

A number of sources agree that the true thermal capacity of a transmission line is considerably higher than the rated values [1-5]. This is applicable for power systems with short to medium lines where thermal capacity as opposed to stability limit is the limiting factor to line capacity. Dynamic line rating (DLR) can be used in an assessment to temporarily relax the line limit constraints and alleviate network congestion due to short periods of high wind power output. However, incorporating DLR into system studies and optimization is challenging since it leads to uncertainty in constraints. Most of the power system applications of optimal scheduling problems model line power transfer limits as deterministic values and place less emphasis on dynamic variation in line capacity. An alternative to this is chance constrained optimization which allows some flexibility in the constraint satisfaction by allowing constraint violation, provided their probability is limited to a specified value. [6, 7]

This paper presents how dynamic line rating can be used in an assessment to improve the utilization of wind in congested networks with and without system contingencies. The extent of congestion is quantified as the amount of the variation in LMP over all the nodes and difference in the LMP profile from the uncongested base case. The effectiveness of dynamic line rating on congestion and wind utilization is determined before and after contingencies. The paper also examines how the level of congestion before the contingency affects the effectiveness of DLR. The extended conic quadratic (ECQ) approach presented in [8] is used for optimization. It is modified to include dynamic line ratings.

II. Dynamic Line Rating

A. Stochastic Optimisation with Dynamic Line Rating

The actual maximum capacity of a line can vary depending on a number of factors, which are mostly related to the weather. The probability distribution of line capacity is modelled by the generalized extreme value distribution [3, 9] and the rated line capacity is on the lower end of the possible range of capacities.

There are other models which use weather data as an input to determine the DLR [1, 2, 4]. The probability distribution method approximates these models with good accuracy and the amount of data required to build this model is highly reduced. Some correlation is expected between wind speed and the cooling of the line and this is partly captured by the probability distribution of line capacity. Due to the distances covered by lines, the weather conditions vary considerably in different parts of lines [4]. The dynamic capacity is limited by regions where cooling due to wind is low. The approach can also accommodate different models which use weather inputs to determine DLR.

The parameters of the distribution are determined according to the rated maximum limit on transmission lines. Based on the analysis in [1] most utilities load their lines such that the probability of exceeding the rated capacity ranges from 20 – 30%, depending on the season. Thus it was assumed that the probability of exceeding the rated capacity was 25% and an inverse distribution was used to determine the parameters for the probability distribution. The actual probability can vary depending on the utility but it is straightforward to perform the analysis with a different value. A more detailed study might treat this as a variable function. The objective function incorporating DLR as a penalty function with stochastic elements is shown in (1)

$$f(x) = C_g(P_g) + C_W(P_W) + C_{DLR} + C_{congestion} \qquad (1)$$

where $C_g(P_g)$, $C_w(P_w)$, C_{DLR} and $C_{congestion}$ represent cost of conventional generation, cost wind (including reserves), cost of dynamic ratings, and cost of congestion respectively. $C_g(P_g)$ and associated constraints of conventional OPF (optimal power flow) problems are given in [8, 10-12]. $C_w(P_w)$ is the cost of uncertainty due to wind, which can be incorporated into OPF by using stochastic optimization and is given in [8]. The problem is solved by transforming to a conic quadratic optimization problem and using an interior point method [8, 13]. This has the advantage that the objective function becomes quadratic and almost all the constraints become linear. These transformations are not system dependent and hence can be applied directly without a modification.

B. Cost of congestion and cost of DLR

To account for DLR, the problem was modified to include uncertain constraints. The penalty in (2) was imposed on violating the line thermal limit constraint and included in the objective function thereby transforming it into a 'soft' constraint.

$$C_{DLR} = \sum_{p=1}^{N_L} \sum_{q=1}^{N_L} \left[c_{OLp} \left(\sum_{k=1}^{N_k} h_{pq,k} a_{pq,k} \right)^2 \right] \qquad (2)$$

The total number of lines in the system is N_L and p-q represents a line from bus p to bus q. The cost of violating the constraint is proportional to the magnitude by which actual line flow exceeds the line capacity. The constraints in (3) complement the additional terms in the objective function to account for the cost of uncertainty in stochastic line rating.

$$\begin{aligned} &a_{pq,k} \geq s_{\max,pq,k} - S_{sch,pq} \\ &P_{local,n} \leq P_{D,n},\, a_{pq,k} \geq 0,\, P_{local,n} \geq 0, \end{aligned} \qquad (3)$$

$S_{sch,pq}$ is the expected value of power transfer limit of line p-q. The actual thermal capacity of line p-q is a random variable which is discretized and represented by the ordered pair ($h_{pq,k}$, $s_{max,pq,k}$). Each discrete value (represented by index k) of $s_{max,pq,k}$ has corresponding probability $h_{pq,k}$ and there are a total number of N_k ordered pairs. The term $a_{pq,k}$ (with per unit cost c_{OLp}) represents the overload and it corrects any violation in the constraint $S_{sch,pq} > s_{max,pq,k}$. While the actual value of c_{OLp} will depend on the system the relative value is set so that it is much higher than the other cost coefficients in the system (of the order 10^3) to reflect the cost of DLR.

When network congestion occurs there is an inadequate capacity to transport low cost generation to loads. These loads then have to use local reserves to supply the demand usually at a much higher price. Alternatively, the load may have to be shed which also results in costs to consumers and often penalties to the utilities. The cost of local reserves or penalty of shedding load is assumed to be the main contributor to cost of congestion which is given by (4).

$$C_{congestion} = \sum_{n=1}^{N} c_D P_{local,n} \qquad (4)$$

$P_{local,n}$ represents any adjustment of load (by calling on local reserves or load shedding) at bus n (where the total number of buses is N). $P_{local,n}$ is required to balance the system when congestion has occurred but it comes at a high cost per unit (c_D). Cost of network congestion can also be due to assets being overloaded leading to reduced life, volatility of electricity prices, and loss of revenue for generators since they cannot sell energy.

The short term cost of overloading lines is a result of the risk of thermal overload. Additionally, repeated overloading can stress the assets leading to reduced life and an increased cost in the long term. For low levels of overloading, the risk of thermal overload is expected to be negligible but as the dynamic line rating increases, it can rapidly increase for moderate to high levels of overloading. The cost of DLR is the expected cost due to an outage in the line as a result of thermal overload. Non-linear approximation of DLR cost requires applying weighting factor or artificial intelligence based methods to integrate the overall risk of asset overloading into the formulation. However, a quadratic function was used to approximate the cost of DLR as this has the features described and would lead to relative ease of determining the Jacobian and Hessian matrices.

An example of DLR cost and linearized network congestion cost is shown in Fig. 1. Initially, the cost of DLR is less than the cost of network congestion. However, only a limited amount of DLR is possible because system assets cannot be overloaded infinitely. Hence, after the DLR limit point, it is more cost effective to protect system assets and mitigate congestion by locally supplying loads or shedding loads at worst case. The DLR limit point will be determined by the values of congestion cost (cost of local supply / load shedding) compared to cost of DLR for the system under consideration.

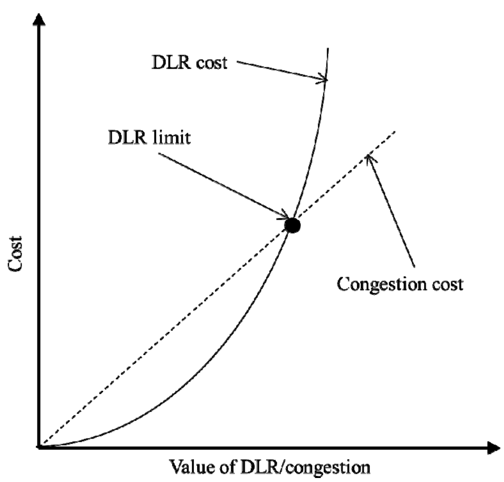

Figure 1. Comparison of DLR cost and network congestion cost

This approach linearizes the cost due to the local reserve generation that supplies shortfall in generation that cannot be transported. These are smaller generators with minimal startup cost and a much smaller output range compared to large generators. Thus, the cost of operation can be assumed to be linear and directly proportional to the output. The overall cost of network congestion is a broad concept and encompasses cost of unsupplied generation, additional cost to customers, long term asset de-rating and the associated importance of each factor. In addition, non-linear approximation requires applying weighting factor or artificial intelligence based methods to integrate the overall cost of network congestion into the formulation.

III. Case Studies

A. *Modified IEEE 14 bus system*

Fig. 2 shows the IEEE 14 bus test system with integrated wind plants. There are two wind farms that are connected at buses 6 and 8. The two wind farms are based on the actual wind farms in Albany and Emu downs which are located in Western Australia. The parameters for the wind farms are summarized in Table I.

Table I Wind farm parameters

Description	Wind farm 1	Wind farm 2
Capacity	80 MW	20 MW
Weibull parameters (c, k)	(7.8, 2.8)	(7.23, 2.35)

The Weibull parameters for the two wind farms are based on actual data from the wind farms. They are more than a distance of 600 km apart and spatial correlation is expected to play a negligible role. 1000 random numbers with a weibull distribution are generated and by comparing the relative frequencies, the discretized wind power output distribution is determined.

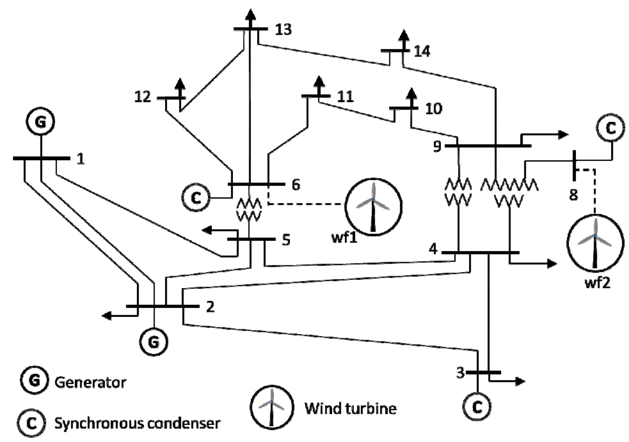

Figure 2. Modified IEEE 14 bus test system with wind turbines

B. *Results and analsyis*

The first test established the base case scenario, without any contingency in the system with LMP profile shown in Fig. 3(a).

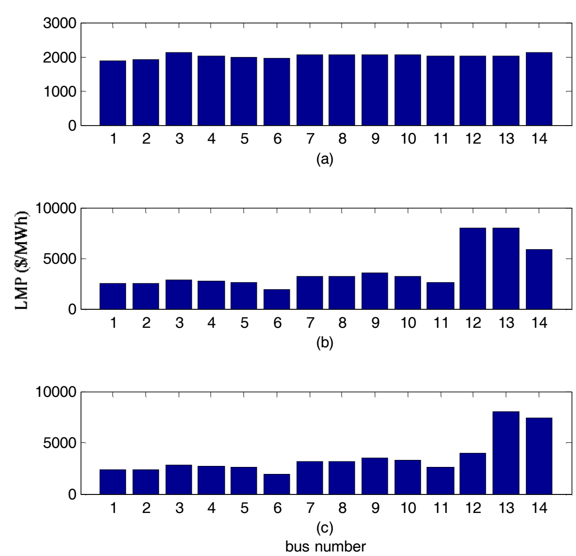

Figure 3. LMP profile (a) before congestion, base case (b) Line 6-12 removed (c) Line 6-12 removed but with dynamic asset rating –check y axis and units

Fig. 3 (a) shows minimum variation in LMP indicating no congestion. Fig. 3(b) shows the effect of an outage in line 6-12 on the LMP profile which shows a significant rise in LMP in nodes 12, 13 and 14. Fig. 3(c) shows that DLR reduces the LMP in node 12 thereby reducing network congestion but does not eliminate it completely. To compare several LMP profiles quantitatively the term LMP_V is defined by (5).

$$LMP_V = \sqrt{\sum_{i=1} \left(\frac{LMP_i - LMP_{i,base}}{LMP_{i,base}} \right)^2} \tag{5}$$

LMP_V compares the LMP of a given test case with the uncongested base case in Fig. 3(a) ($LMP_{i,base}$). The difference between LMP at each node i is determined and the average of this gives the average difference in LMP across the system compared to the base case. LMP_V compares the difference in LMP profiles but does not necessarily consider the cause of the LMP variation or detailed analysis of the LMP profile. Fig. 4 shows the line percentage loading profiles.

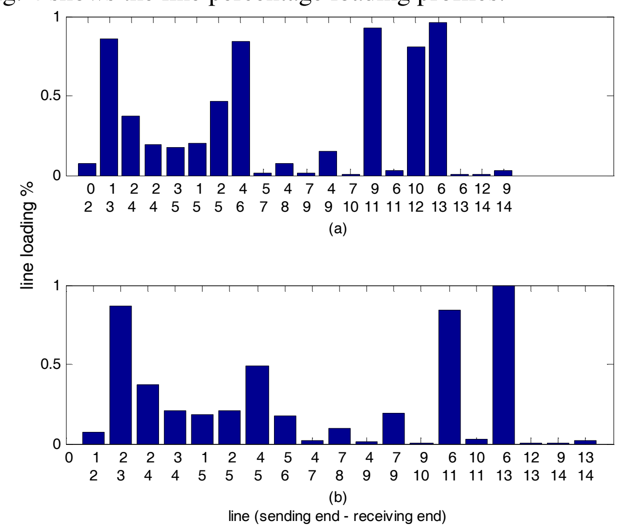

Figure 4. Line loading percentage (a) base case (b) after outage in line 6 – 12. Write y-axis for both

Fig. 4(a) shows the line loading profile for the network under normal conditions (without any contingencies). Under normal operating conditions, all the lines connected to wind farm 1 are loaded to 85% - 98% of full capacity.

After an outage, line 6 – 13 is at 100% capacity (Fig. 4(b)) and congestion results as seen in Fig. 3(b). The spare capacity is measured as the total available capacity expressed relative to the total rated capacity of all lines and is determined by equation (6).

$$spare\ capacity = \frac{\sum_{critical\,lines} (I_{\max} - I_{flow})}{\sum_{critical\,lines} I_{\max}} \tag{6}$$

Where I_{max} is the magnitude of maximum current in a line and I_{flow} is the magnitude of current actually flowing in the line. Spare capacity is calculated for all the critical lines in the system which are identified as those connected directly to bus 6 (the wind bus). These are defined as critical lines because these lines are loaded close to their full capacity and likely to be congested in the event of contingencies.

Fig. 5 shows the generation mix which indicates curtailment of wind as a result of congestion. The output of wf1 is curtailed when the line 6 – 13 experiences an outage. When the dynamic rating of assets is considered it restores the scheduled wind output to the pre contingency value. In this case, if the DLR is incorporated for the assessment/ decision-making process then the post-contingency impact on wind farm output can be eliminated.

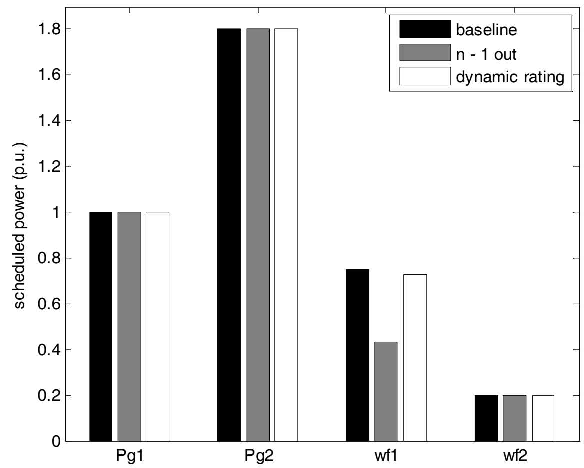

Figure 5. Generation mix under different conditions

Wf2 is not affected by the contingency because the congestion is localized to wf1. The wind curtailed is normalized with respect to the wind generation in the uncongested base case and determined by equation (7).

$$wind\,curtailed = \frac{P_{w,base} - P_w}{P_{w,base}} \tag{7}$$

Table II summarizes the effect of different outages on the system. Only outages resulting in significant congestion are reported in Table II.

TABLE II. COMPARISON OF CONGESTION WITH AND WITHOUT DLR

Case No.	*line out*	**No DLR**		**with DLR**		*spare capacity required to match DLR*
		LMP_V	*WC*	LMP_V	*WC*	
1	none	0.0	0%	0.0	0%	-
2	6-11	6.07	8%	2.21	1%	18%
3	6-12	5.07	13%	0.52	1%	22%
4	6-13	8.05	33%	4.54	2%	54%
5	6-11, 6-12	6.52	23%	2.81	2%	26%
6	12-13, 6-13	6.87	34%	4.09	8%	27%
7	13-14, 6-12	6.20	14%	2.37	1%	24%
8	12-14, 6-13	7.50	33%	4.04	5%	44%

WC = wind curtailed

It is seen that DLR reduces congestion (although doesn't eliminate it completely) and reduces wind curtailment. The line loading is shown as a percentage of line capacity for each line in Fig. 4. When outages in critical lines are considered, the reduction in average LMP_V ranges between 43 – 64%, with exceptional cases of being as high as 89% (case 3). Congestion in a line is not always due to physical thermal limits. In some cases the line may not be at the thermal limit, but further power flow through the lines would cause voltage drops that would violate constraints. As a result the flow through the line is limited. This is the reason why DLR cannot completely eliminate congestion. In cases where non critical lines with low levels of loading experience an outage, the increase in LMP_V would be negligible and dynamic line rating would have limited effectiveness.

For comparison, Table II presents the amount of spare capacity that would be required to reduce congestion to the same level as DLR. Thus, dynamic asset rating can allow the cost of network reinforcement to be deferred. In the presented cases, if a worst case scenario design were to be carried out, then 54% of spare capacity would have to be built into the system to provide the same benefit as DLR (outage of line 6 – 13 as per case 4).

Table II also showed that while some N – 2 outages lead to higher value of LMP_V compared to the corresponding N – 1 outage this is not always the case. For example when 6 – 13 is out (N – 1) LMP_V is 7.3% higher than when 12-14 is also out. While this would initially indicate a higher level of congestion with the N – 1 outage as opposed to the n-2 outage a closer examination of the LMP profile is required. Fig. 6 shows the LMP profiles of an (N – 1) outage (case 4) and an (N – 2) outage (case 8).

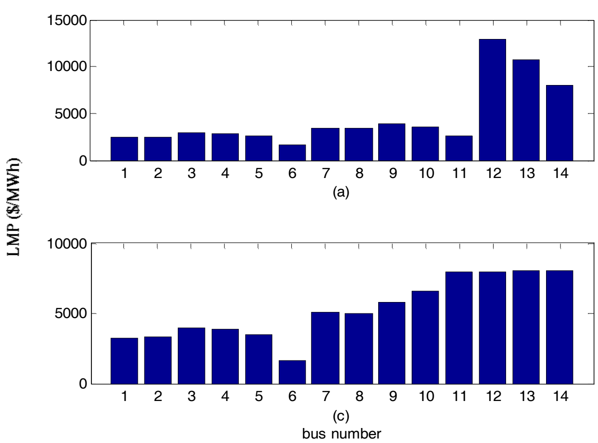

Figure 6. Comparison of LMP profiles (a) line 6-13 out (N-1) (b) lines 12-14 and 6-13 out (N-2)

While the LMP profile in fig. 6(a) is generally flatter the three nodes (12, 13, 14) with a higher LMP skews the average LMP variation. In fig. 6(b) the average difference to the base line case may be smaller but more nodes have a higher price than the base case. So the N – 2 outage leads to higher LMP in more buses even though the increase in LMP per bus is lower than the N – 1 case.

IV. Conclusion

This paper has demonstrated how the incorporation of dynamic asset rating can alleviate post contingency network congestion, releasing a considerable latent capacity to limit the curtailment of wind. The test case showed that DLR provides similar benefits to a 54% capacity expansion at a fraction of the cost. Simulating both N – 1 and N – 2 contingencies showed the adaptability and utility of dynamic line ratings in addressing network congestion under a wide variety of situations. The proposed approach can be used to quantify the level of differed investment that can be achieved by incorporating dynamic line ratings while limiting the post contingency risk.

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